Journal Of Financial And Strategic Decisions
Volume 8 Number 2 Summer 1995

THE IMPACT OF FIRM'S CHARACTERISTICS ON JUNK-BOND DEFAULT

Sam Ramsey Hakim* and David Shimko**

Abstract

This study examines firm-specific value and risk factors as early predictors of junk bond default. Reduction in equity value, increased variation in long-term debt levels, and reductions in cash flow are found to be statistically significant indicators of higher default probabilities in a logit model. Variations in investment levels have insignificant explanatory power. The model provides individual investors with the ability to assess the default risk of high-yield securities based on the levels of observable financial variables.

INTRODUCTION

Recently, much academic and regulatory interest has been concentrated on the problem of high-yield, junk bond default. Arguably, corporate bonds have defaulted for many reasons, including factors specific to the individual issuing firm, variables corresponding to the industry in which it operates, and macroeconomic forces affecting the business cycle. Individual factors include the firm's leverage, industry type, agency problem, riskiness of the investment decisions, managerial integrity, efficiency and investment savvy together with institutional operating costs. Industry and aggregate factors affect the firm's performance and therefore affect default as well. This paper tests the significance of the firm's characteristics on the likelihood of default and assesses their relative impact on future default rates.

Bonds are considered high yield (or junk) based on the credit ratings they receive from the two major US rating agencies, Moody's and Standard & Poor's. Any bond rated below Baa3 by Moody's or BBB- by S&P is included in the high yield universe. High yield bonds are classified in two ways, as "fallen angels", which are former investment grade bonds that have declined in ratings, and as new issue high yield bonds, which are issued generally by young, growing companies in recapitalizations. The growth of the market has been exceptional. According to estimates by Drexel Burnham Lambert (1989), the size of the market grew from $15 billion in 1976 to almost $200 billion in 1989. At the end of 1988, high yield bonds represented an estimated 25% of the entire corporate bond market.

The remainder of the paper is organized as follows. In section II and III respectively, we discuss the significance of default in bond valuation and provide a brief review of related research. In Section IV, we introduce the warning signals of default, present the proposed methodology and describe the data for the study. The methodology is applied in section V and a statistic is derived in section VI to test the model goodness of fit. In section VII we discuss the result and provide two examples to show how the model can be put to use by individual investors. Section VIII concludes the paper.

---

*University of Nebraska, Omaha.
**University of Southern California.
We would like to thank Joseph Bencivenga of Salomon Brothers and Melvin Vukcevich of Kemper Securities Group for helpful comments.

BOND DEFAULT AND ITS SIGNIFICANCE

Like many fixed-income investments, junk bonds are exposed to two principal risks: interest rate risk and credit risk. The former arises from the fact that a bond locks in an investment at a fixed promised coupon rate for a period of time during which the market rate is constantly changing. Therefore, a rise in interest rates will have an adverse effect on the investor's holding-period return. The credit risk is generally evaluated by considering the historical as wells as the expected performance of the borrowing firm. Investors may readily hedge against interest rate changes if the impact of term structure shifts on bond prices is known. However, it is more difficult to hedge against individual defaults, even if default probabilities are systematic. As the market's understanding of interest rate risk increases, the greater marginal benefit derives from a better assessment of the default risk.

The estimation of junk-bond default plays an important role in determining the net worth and financial viability of savings and loan institutions, which own an estimated 14 percent of the junk bonds outstanding (about $30 billion). Under the new savings and loan bailout plan, thrift institutions are required by government to phase out their junk bond holdings by 1994. A better understanding of the default premium in junk bonds will enable regulators to assess the valuation and risks of the asset portfolios of savings and loans more accurately.

Finally, bonds represent a major instrument firms employ to raise their capital. This is supported by the fact that the bond market dwarfs the stock market by a ratio of three to one. With more accurate information on default rates, investors can measure their asset portfolio risks and assign appropriate default risk premia to junk bond investments.

REVIEW OF PREVIOUS MODELS

Prior studies on junk bond default include the work of Hickman (1958) who provided exhaustive statistics on annual default rates and holding period returns to bond holders from 1900 to 1949. His work was subsequently updated by Atkinson (1967) using the same approach. More recent work by Altman & Nammacher (1985) has focused on the incidence of default in the high yield bond market. These studies concluded that the average annual default rate is in the one to three percent range. To compensate the investor for this default risk, these studies found the average spread of yields between quality and junk bonds to have fluctuated between three and five percent, which has more than offset the default risk premium implicit in junk bonds. These studies have lead to the conviction that the high yield debt market had low risk-adjusted default rates (or a return higher than the risk premium).

Explanations for the yield premium derive from several sources. The market may underprice junk bonds because of an investment stigma, or because of popular, government and institutional pressure and restrictions against holding junk bonds. Analysts may not have properly calculated the value of the firm's call option on its high yield debt. The callability option is likely more valuable for a junk bond than for a higher grade bond; junk bonds are called when a firm's fortunes improve, in addition to the firm's usual refinancing motives. Finally, if default probabilities vary systematically, one would expect a yield premium on these bonds. The systematic default theory was supported in September 1989 by the high yield market shake-out. According to the Wall Street Journal, in a single day (9/14/89) many bonds lost 20% of their value.

The aforementioned studies measured *annual* default rates and therefore failed to account for the age of the bond. As a result, these studies overlooked the possibility that default rates may not be stationary through time, but are likely to change as the relatively newly issued, lower-grade bond matures and the average age of the lower-grade bond universe increases.

In his most recent paper on junk bonds, Altman (1989) used a mortality rate concept to measure default rates conditional on the age of the bond.. Altman found that the cumulative bond mortality increases with the age of the bond and can reach as much as 32 percent for B-rated bonds over a ten-year period. The Altman (1989) technique was also adopted by Asquith et al. (1989) who measured default rates on lower-grade bonds but expand on Altman's (1989) definition of default. Asquith et al. (1989) reported default rates substantially higher than those implied by earlier work and hinted that the lower-grade bond market may be riskier than previous work would have lead one to conclude.

Blume & Keim (1991) argue that if investors underestimate the probability of default when bonds are originally issued, the realized returns on older bonds may be less than those on newly issued ones. Consequently, in a market dominated by new issues, the returns could be overestimated. Based on the cohort of bonds issued in 1978, they find a significant relation between the bond age and default rates. However, because default rates vary with economic conditions, Blume & Keim admit that their earlier result may be controversial. After adjusting for the systematic variation in default rates over time, they reexamine this relationship and conclude that there is little statistical evidence to support a correlation between the bond age and default. But regardless to any aging effects, a junk bond's default rate depends critically on the firm's performance. To investigate this relationship, this paper expands on the preceding works by employing a new methodology. The study uses bond credit ratings, firm's cash flows, total debt, market value and investment decisions to uncover the risks specific to each firm. Then, knowing the firm credit risk, the study will attempt to determine how far these variables would have to move in order to drive the issue into default. The end product is an empirical and comprehensive, early-warning model for bond default.

WARNING SIGNALS OF DEFAULT

The definition of default can have a wide spectrum of interpretations. In this paper, the definition of default is based on the same criteria adopted by S&P in rating the outstanding bonds of public firms. Precisely, an institution is defined to be in default on its debt if its bond rating falls to "D" on the S&P scale at any point in time during the sample period from 1980 through 1989. The bond ratings pertain to specific issues determined by S&P to be the most representative of the company's creditworthiness. Clearly, these ratings are not stationary over time, but are expected to vary with the firm's financial performance and the business cycle.

Our data includes a random sample of 147 public companies with outstanding bonds rated below BBB- by S&P. All data, including the firms' financial information, comes from Standard & Poor's Compustat. Clearly the sample doesn't represent the entire universe of junk bonds. To compensate for the sample size, however, the companies are tracked over a 10 year time period. The data is updated quarterly to reflect changes in the firms' financial condition over 39 time periods starting from the first quarter of 1980 through the third quarter of 1989. For failed companies, the financial data is computed for the quarter of default. For all other companies (those that remained alive) the data is computed for the last quarter of the study.

The data is also diverse. For example, the sample contains firms which, over time, showed signs of financial improvement, and consequently had their rating upgraded. The data also includes "fallen angels" which are former investment grade bonds that have declined in ratings. Of the 147 companies in the sample, 24 firms had defaulted on their bonds at one point, while others are -or were- rated below BBB- during the time period of the study. From Table 1, it appears that more than 83% of the bonds rating fell into the C category (CCC, CC, C, CCC+, CCC-) immediately prior to default. The CCC rating alone accounts for the largest single grade prior to default. A little less than 17% of the bonds in the sample were rated in the B category (B, B$^-$) immediately before D. Of the 24 companies that fell into default, four had reemerged under with a rating other than D. Virtually all the defaulting companies analyzed in the data set had their bond rating downgraded by S&P prior to default. Table 2 presents the details of the sample bond rating at time of origination and the third quarter of 1989. From exhibit II, approximately 10% of the companies in the sample were originally rated in the A category, 76% were rated B, and 14% were rated C.

The first variable proposed for the model is the firm's cash flow, which, by falling, may signal the beginning of forthcoming financial difficulties. Because a firm's overall risk hinges on the success of its projects, we expect the risk of default to vary directly with the firm's cash flow. Indeed, when a project turns sour and the cash flow is reduced, a firm would find it increasingly difficult to honor its debt obligations on time. As a result, it is expected that the probability of default to be negatively correlated with the firm's cash flow. Instead of relying on the absolute cash flow, the study uses the cash flow margin which is computed as the sum of quarterly net income before extraordinary items and quarterly depreciation and amortization, divided by quarterly net sales. This is then multiplied by 100 to yield a percentage figure.

In general, default is caused by the firm's inability to meet its debt obligations in a timely fashion. At the time of default, however, firms tend to have large outstanding debt. The management of a firm with high default risk is likely to issue more long-term debt to meet its payment obligations in an attempt to gain time. Therefore, by analyzing the behavior of a firm's long-term debt, we hope to be able to explore its impact on the risk of default. We posit that the default risk is an increasing function of the size of the debt. Our argument rests on the belief that a firm is likely to finance risky projects by issuing new debt as opposed to equity. For low-risk projects with a high net present value, the management of a firm acting in the shareholders' best interest would want to reap the entire expected profits and not share them with new shareholders if equity financing is adopted. By issuing bonds, shareholders promise a fixed payment to bondholders and guarantee to themselves the total profit of the project. Therefore, a rise in the firm's debt[1] over time may be interpreted as the beginning of more risky investments to follow and consequently a larger overall risk of default. Because a company would tap the capital market and raise funds long before the results of its projects become known, the firm's *current* debt may not capture the entire effect. Instead, we compute the standard deviation of long-term debt levels during the two-year period prior to default. Since the amount of a firm's debt is likely to be proportionate to its size, we adjust the variation of debt by the book value of the firm. The larger the variation of debt, the more likely that default will ensue.

Closely related to long term debt is the effect of long-term investment. We posit that a firm is likely to raise the level of its investment[2] activity when its overall risk rises. That is to say, stockholders wary about default risk might accept investment projects they would otherwise decline in an effort to regain financial stability. This would be even more significant when the increase in investment is fueled with further debt, perhaps indicating that the firm is gambling with its future by using its bondholders' funds.

To capture the remaining default risk, we also propose to look at the firm's market value at the time of default. Perfect market behavior implies that, prior to default, the share price of a firm will fall by an amount large enough to reflect the increased riskiness of default as perceived by the marginal investor. The larger the default premium, the lower the market price of the stock. Therefore we would expect a strong negative correlation between the probability of default and the firm stock price. Because the firm value will vary with its size, we adjust the market value[3] by the firm book value. The market-to-book ratio provides an indication of how investors perceive the firm. Institutions with relatively high rates of return on equity generally sell at higher multiples of book than those with low returns. In short, the lower the market value relative to book, the higher the probability of default.

For those companies that never defaulted, all the financial variables discussed above are measured at the end of the time period of the study (3rd quarter of 1989).

EMPIRICAL ESTIMATION

Based on the warning signals discussed above, we construct a vector of regressors which we incorporate within a logit regression model of the type:

Equation 1

$$\mathrm{Ln}(y_i) = \alpha_0 + \beta_1\,\mathrm{MRK/BK} + \beta_2\mathrm{CASHFLOW} + \beta_3\,\sigma(\mathrm{DBT})/\mathrm{BK} + \beta_4(\mathrm{INVESTM}) + \varepsilon_i$$

where y_i is the odds ratio $p_i/(1\text{-}p_i)$, p_i is the probability of default and $p_i = 1$ if the firm's bond has fallen to a D grade and is 0 otherwise. Note that the logistic regression model requires fewer assumptions than the common linear probability model: $p = X\beta + \varepsilon$. In addition, the linear model has a major shortcoming: predictions based on the linear version sometimes have no interpretation. For example, using the estimated vector ß and multiplying it by a forecast design matrix, the model can predict default probabilities p_{it} that can be either negative or greater than one. However, this shortcoming can be easily overcome when the model assumes a logit function which generates predicted posterior probabilities between 0 and 1. This is the essence of the approach adopted in this paper. The model is estimated by the method of maximum likelihood. Under certain assumptions (see Amemiya 1989), the estimated coefficients of the model are asymptotically normally distributed. This last property is used to compute chi-square statistics to determine the level of significance of the variable coefficients included in the model.

TESTING THE MODEL GOODNESS OF FIT

To test the model goodness of fit, we also compute the model likelihood ratio. We rely on a statistic based upon the model chi-square. This is computed by taking twice the difference in log likelihood of the current model from the log likelihood based on no variables which is then used to construct a statistic, R, similar to the multiple correlation coefficient in a regression analysis. R is defined by:

Equation 2

$$R = \{(\chi^2 - 2k) / [-2\Lambda(0)]\}^{1/2}$$

where χ^2 is the value of the model chi-square, k is the number of regressors in the model, and $\Lambda(0)$ is the value of the log likelihood with no variables. The second term in the numerator of the R statistic expression in (2) above is subtracted to penalize for the number of parameters estimated. If this correction is ignored, R^2 can be interpreted as the proportion of the log likelihood explained by the model, and R would fluctuate in value between 0 and 100%. From Table 3, we find that the model R is 46%. That is, the regressors chosen explain about 46% of the total default risk in the data. We also report partial R statistics defined to be:

Equation 3

$$\rho = \{(\text{Variable } \chi^2 - 2) / [-2\Lambda(0)]\}^{1/2}$$

Here, if the -2 correction is ignored, the ρ's indicate the contribution of each individual variable to the default risk, independent of the sample size. The ρ statistic is equal to 0 if the variable makes no contribution to the model and +1 if the variable is perfectly positively related to the probability of default in the dependent variable and -1 if its perfectly negatively related.

RESULTS

The results of the study indicate that high default-risk institutions tend to have a significant variation of debt prior to the default announcement. As the overall debt balance rises above its normal level, the firm must meet the heavy burden of debt payments making the institution vulnerable to default risk. Even if default is imminent, a firm may still try to gain time by increasing its debt levels to pay off those that are due. A closer look at the firms in the data set reveals that defaulting companies had almost all borrowed significantly during the two-year period which preceded default. These results support the viewpoint that the default risk increases with the amount of the outstanding debt.

The results of the cash flow variable show a strong negative correlation between the cash flow margin and the risk of default. The probability of default seems to be log-linearly correlated with the firm's net income and net sales. Lower income and/or net sales inflate the default risk. From Table 3, we notice that the highest ρ value is obtained by the cash flow variable. This variable by itself explains about 21% of the total default risk explained by the model.

The findings of the equity variable suggest that a high bond default is generally preceded by a falling equity. As expected, the market price of the firm stock will reflect the riskiness of its investments, operations and ultimately its solvency. The behavior of the market to book value alone accounts for 18% of the total variation in default explained by the model.

The results of the investment variable, however, suggest a different interpretation. While the firm's debt may be mounting prior to default, the level of its investments level seem relatively stable and consistent. That is, the data do not show any significant change in investment activity prior to default. This is supported by the statistical insignificance of the investment coefficient in explaining the variation of default across the companies in the sample. It would seem that defaulting firms did not use the proceeds from the sale of their bonds to finance an expansion of their investment projects.

Illustrative Examples

As an example of how the model could be applied for predictive purposes by individual investors, consider the following real data on 2 different firms:

1. Texscan Corporation:

Standard Deviation Of Long-Term Debt	\$ 14.000M
Average Increase In Investments	\$ 0.022M
Market Value	\$ 20.340M
Average Book Value	\$ -5.460M
Cash Flow Margin	-83.57

Noting that the model:

$$\mathrm{Ln}[p_i \;/\; (1-p_i)] \;=\; X_i\beta$$

can be transformed to:

$$p_i \;=\; 1 \,/\, [1 + \exp\{-X_i\beta\}]$$

we have from Table 3, and the following estimated equation:

$$p_i \;=\; [1 + \exp\{1.37 + 0.025\ \mathrm{CASHFLOW} - 0.271\ \sigma(\mathrm{DBT})/\mathrm{BK} + 0.595\ \mathrm{MKT}/\mathrm{BK}\}]^{-1}$$

The model predicts a probability of default of about 90%. Naturally, the model often may over-predict or under-predict, but companies with similar characteristics would, on average, achieve a default probability of 90%.

2. Alleco Incorporated:

Standard Deviation Of Long-Term Debt	\$ 58.300M
Average Increase In Investments	\$ 51.210M
Market Value	\$ 0.010M
Average Book Value	\$ 9.788M
Cash Flow Margin	80.95

Based on this data, the model predicts a probability of default of 14%.

CONCLUSION

Using a sample of 147 public firms with outstanding bonds rated below BBB- on the S&P scale, our study addresses the question of whether bond default could be predicted. If a set of warning signals can be identified, investors might reassess the magnitude of the default premium they require on low-grade securities.

While ratings tend to lag performance indicators, we have shown that important warning signals exist for individual junk bond defaults. While we have ignored macroeconomic and regional variables, we have shown the impact of these variables if they affect the operating characteristics of the firm. The default likelihood is higher for firms with large variation in debt, a low cash flow margin and a declining market value. Our model however fails to point to any significant change in investment activity prior to default. Finally, we make no statements about the pricing of debt; our analysis is consistent with efficient market behavior.

TABLE 1—EXHIBIT 1
Defaulting Companies Rating Prior To Default

Bond Rating	Number
B	2
B-	2
CCC+	1
CCC	9
CC	4
C	6
Total	24

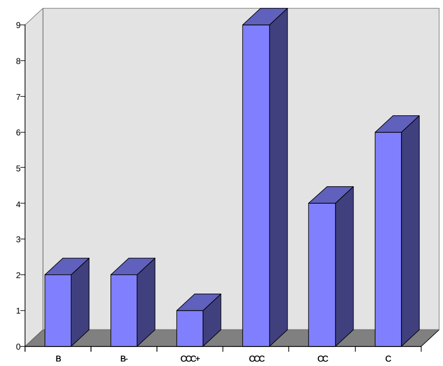

TABLE 2—EXHIBIT 2
Bond Rating Of Sample

Rating	Original	Ending
AA+	1	0
AA	2	0
AA-	1	0
A+	3	0
A	8	4
A-	0	2
BBB+	1	1
BBB	2	4
BBB-	2	5
BB+	2	8
BB	5	3
BB-	8	7
B+	17	12
B	26	9
B-	49	47
CCC+	5	6
CCC	13	9
CCC-	0	1
CC	2	3
C	0	4
D		20*

*Four out of 24 defaulting companies came out of default

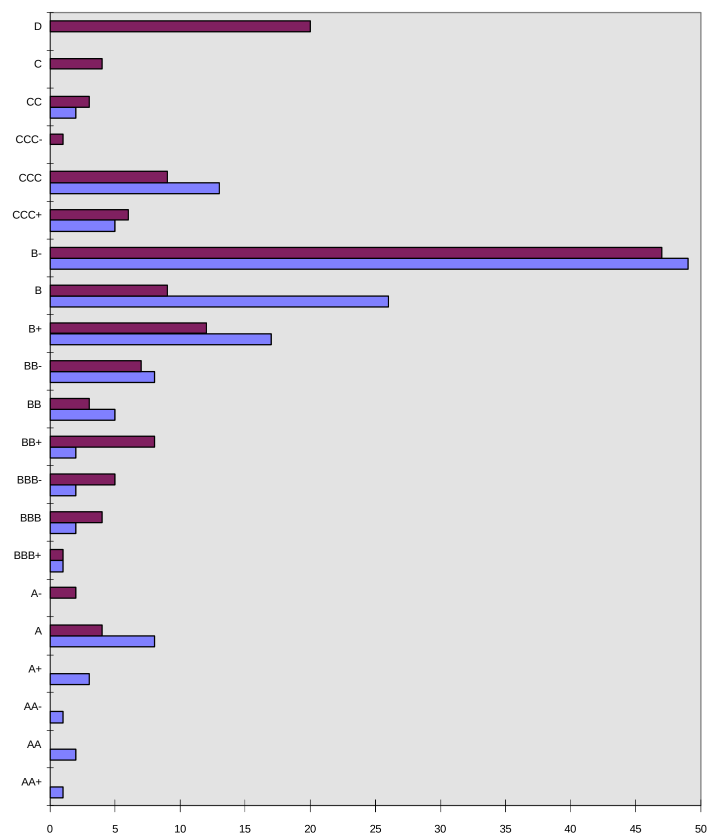

TABLE 3
Logistic Regression Procedure

Dependent Variable: **DEFAULT**
147 OBSERVATIONS: 123 Alive, 24 In Default.

Variable	Mean	Minimum	Maximum	Std. Deviation
MKT/BK	2.03221	-3.72764	31.6736	3.60506
CASHFLOW	-1.17952	-173.19	80.95	31.742
σ(DBT)/BK	0.593224	-2.91001	10.9396	1.83578
INVESTM	7.16713	0	107.33	19.6849

Maximum Likelihood Estimates

$$\ln[p_i/(1-p_i)] = \alpha_0 + \beta_1 \text{ MKT/BK} + \beta_2\text{CASHFLOW} + \beta_3\ \sigma(\text{DBT})/\text{BK} + \beta_4\ \sigma(\text{INVESTM}) + \varepsilon_i$$

Goodness Of Fit Statistic: R = 46%

Variable	Beta	Std. Error	Chi-Square	P-value*	ρ
Intercept	-1.3696	0.3544	14.94	-	-
MKT/BK	-0.5950	0.2334	6.49	1.08%	-0.185
CASHFLOW	-0.0249	0.0090	7.74	0.54%	-0.210
σ(DBT)/BK	0.2715	0.1400	3.76	5.25%	0.116
INVESTM	0.0007	0.0136	0.00	96.0%	0.000

*P-value based on this chi-square with one degree of freedom.

Covariance Matrix Of Estimates

	Intercept	MKT/BK	CASHFLOW	σ(DBT)/BK	INVESTM
Intercept	0.1255756	-0.0395704	0.00142521	-0.0210313	-0.00118089
MKT/BK	-0.0395704	0.05451295	-0.000606171	-0.00360270	-0.000171603
CASHFLOW	0.00142521	-0.000606171	.00008037296	-0.000177284	-.0000113517
σ(DBT)/BK	-0.0120313	-0.00360272	-0.000177284	0.01959639	0.0001061681
INVESTM	-0.00118089	-0.000171603	-.0000113517	0.0001061681	0.0001855533

ENDNOTES

1. Our definition of debt represents obligations due more than one year from the company's balance sheet date. It includes bonds, mortgages and similar debt; obligations that require interest payments and notes payable due within one year and to be refunded by long-term debt when carried as a non-current liability. We adjust for the firm size by dividing the total debt by the firm book value averaged over the last four quarters prior to default.

2. This represents funds used to increase a company's short- and long-term investments in addition to changes in long-term receivables. These funds are then averaged over the four quarters which precede the company's default or the last quarter of the study, depending upon whether or not the firm has defaulted.

3. For a defaulting company, the market value is taken to be the monthly close price at the time of default multiplied by the quarterly common shares outstanding. The product is then normalized by the firm average book value over the last four quarters prior to default. For a company not in default, the variables represent the last quarter of the study.

REFERENCES

[1] Amemiya, T., "The Maximum Likelihood, Minimum Chi-Square And Non-Linear Least Squares In The General Qualitative Response Model," ***Journal of the American Statistical Association*** 71, 1976, pp. 347-351.

[2] Altman, E.I., "Measuring Corporate Bond Mortality and Performance," ***The Journal of Finance***, September 1989.

[3] Altman, E.I. and Nammacher S.A., "The Default Rate Experience on High-Yield Corporate Debt," ***The Financial Analyst Journal***, July-August 1985, pp. 25-41.

[4] Asquith P., Mullins D.W. and Wolff E.D., "Original Issue High Yield Bonds: Aging Analyses of Defaults, Exchanges, and Calls," MIT Paper, June 1989, Forthcoming in ***Journal of Finance***.

[5] Blume M.E. and Keim D.B., "Realized Returns and Defaults on Lower-Grade Bonds: The Cohort of 1977 and 1978," ***The Financial Analyst Journal***, Vol 47, No. 2, March 1991.

[6] Drexel Burnham Lambert, ***High Yield Review***, Vol 8, Issue 4, August 1989.

[7] McFadden, D., "Conditional Logit Analysis Of Qualitative Choice Behavior," ***Frontiers In Econometrics***, 1974, pp. 105-142.